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NLP-Based Sentiment Analysis of Social Media Data on Public Perception of Environmental Policies

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Abstract: *The future of any environmental policy all depends on the view of the citizens since the support of its citizens directly acquires the outcome of such a policy; whether to be successful, or not in terms of compliance, political will and long term sustainability. The social media expansion has been more visible and disorganized, polarized and fragmented because of public opinion. The proposed research is based on the concepts of Natural Language Processing (NLP) to conduct a bulk of sentiment analysis of social media information regarding the environmental-related policy debate of carbon taxes, plastic bans and the incorporation of renewable energy. It was chosen to follow the hybrid research methodology approach that would involve both the sentiment classification via lexicon and the machine learning algorithms, including Support Vector Machines (SVM) and deep learning-based Bidirectional Encoder Representations of Transformers (BERT). The social media variables were collected on Twitter (X) and Facebook in 2022-2024, and covered over 1.2 million posts, comments, and hashtags on policy debates. The results indicate that the correlation between the popular view and the policy acceptance is high with the policies on renewable energy having predominantly positive sentiment (+62) and the carbon tax proposals having negative sentiment (-54) referring to the affordability aspect. The temporal trend analysis indicated that there were occurrences of negative sentiment when announcements of political nature and environmental protests were high. The findings indicate the usefulness of NLP-informed sentiment analysis in providing a policy holder with actionable information, policy-based communication, improved stakeholder engagement, and responsive policymaking within the environmental context. The article demonstrates that computational social science can be used alongside existing methods of policy evaluation to offer scalable and real-time monitoring of the social opinion regarding environmental governance.*
Keywords: *Sentiment Analysis, Natural Language Processing (NLP), Social Media Analytics, Environmental Policies, Public Perception, Machine Learning*

I. INTRODUCTION

The connection between the environment and its governance has proven to create one of the most demanding areas of policy research in the 21 st century, with the majority of its governments worldwide suggesting the new policies through the form of carbon tax, plastic ban, renewable energy incentives, and adaptive actions to climate change to prevent environmental degradation and combat climate change. Despite the fact that such policies are designed so that they align with the global sustainability agenda, much of their success in its adoption by the masses who make the majority of people to which the government must be in line with to ensure compliance, political legitimacy and long term achievement depends on the perceptions that the masses hold. Twitter (X), Facebook, and Instagram have become extremely powerful sources, through which citizens can share their opinions, share their experience, communicate their vision of the environmental policy, including which the mass of user-generated content is huge and, it is its content, which creates an impression of the collective opinion on the grand scale. However, this data is extremely unstructured, informal and in the vast majority of cases, noisy and the traditional ways in which the policymakers and the researchers can derive useful information are often limited in scale, time and geographically, surveys, interviews and opinion polls. It is against this backdrop that scenic computing tools like Natural Language processing (NLP) has become a functional tool of computational procedural power that can be employed in a logical sense to carry out an analysis of enormous text in order to establish feeling, to detect feelings and to categorize a view point in an automated and scalable manner. Not only NLP-based sentiment analysis is applicable in grouping social media posts into positive, negative and neutral ones, but also thematic issues, emotional levels and linguistic undertones that are being the foundation of the ongoing public discourse about the environmental governance. The importance of such analysis is that the environmental policies have a polarizing effect on the nature of the debate that ideological, economic, social interests tend to intersect, leading to a large variety of the mass opinion. To exemplify this, whereas the policy concerned with the renewable energy and employment of the green technology is likely to provoke a positive feeling as it is believed that it is conducive to the future sustainability of the environment, and brings more job opportunities, the carbon taxation proposal, as well as the development of even stricter rules regarding the emission volumes, are also likely to attract rather negative emotions as far as these concepts are thought to create more challenges to the economies of house-holds and industries. Similarly, the banning of single use plastics can be celebrated by environmentists and opposed by small business owners as well as the consumers who deem that it is inconvenient and costly. These inconsistencies represent the need of the governments to develop effective policies, yet also partake in data-driven communication policies, based on the diversity of the shared sentiment. The social media customs a preferential opportunity to monitor these opinions in real time, however, the information mass and studies are composed of demand advanced types of analysis, and NLP shall be invaluable. The more recent advances in machine learning and deep learning, such as Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and Bidirectional Encoder Representations of Transformers (BERT) have significantly enhanced sentiment analysis accuracy and scalability to more complex policy arguments by enhancing the ability of NLP to better absorb context and sarcasm and multilingual text in addition to domain jargon.

Despite these achievements, the gap in the usage of NLP as an environmental policy analysis remains quite significant. Most of the above studies on sentiment analysis have focused on business applications such as product reviews, customer satisfaction and brand monitoring but relatively few have been applied in relation to gauging governance, sustainability and climate-based issues. In addition, existing research on the cross of environmental factors utilizing sentiment analysis involve allocation of restricted data set or lexicon-based means which can potentially fail to encompass the contextual intricacies of on-line dialogue. The other gap in the matter refers to time and space of the public opinion: the social media allows following the trend of evolution, yet there are no researches, which would integrate the study of the long-term tendencies, geographic variation, and the influence of significant socio-political events at the time, e.g. international climate summits, national elections, or environmental protests. The lack of scientific studies is why it is held that urgent is the need to conduct interdisciplinary research in an endeavor to bring together the fields of environmental science with the fields of incorporating data on computing linguistics as well as political speech so as to provide policy makers with adoptable information. These gaps are aimed to be addressed by this research paper, as it presents a framework of sentiment analysis based on NLP to be used to analyse information via social media in relation to environmental policies. The analysis focuses on how the population views in different policy areas such as renewable energy, carbon tax, plastic bans, and climate adaptation engagements through the collection and analysis of big data on Twitter and Facebook within the same period, which is 2022-2024. The mechanism serves as a hybridized version of lexicon based techniques and supervised machine learning models and deep neural networks to ensure scalability and contextual performance of sentiment detection. Besides, the temporal analysis, used to trace the dynamics of sentiment indicated by the time, and the event-oriented analysis, used to trace the effects of important announcements, politics roll-outs, or environmental catastrophes on the attitudes of the population figures also become part of the current work. The interplay of these variables allows the multidimensional concept of the meaning of development of the attitude of the masses towards the environmental administration that will not only provide the descriptive but also the predetermining results in predicting further shift in the attitude of the individuals. The work could not only leave an impression in the context of making a contribution in academia but also guide application by policy makers, environmental agencies and the strategists of communication strategies. Real-time sentiment analysis may be used to warn policymakers of what is about to occur to them as a measure on the one hand may be opposed or even supported, so much that changes can be effected on time. To environmental organizations and the proponents of interest, understanding of the emotional and cognitive secondary of the overarching language proves helpful in the production of a campaign that the citizens can identify with and debunk misinformation. Sentiment analysis could inform the development of policy narratives to be less polarized and agreeable, in the case of communication strategists. Lastly, with the employment of NLP and machine learning, this study can become the paradise between the world of policy-making and ordinary citizens because data-driven approaches can bridge the divide between them. The study, thereby, does not just add to the methodological maturation of sentiment analysis, but contributes to the result of the democratic engagement and sustenance in the digital epoch of environmental government.

II. **Releated Works**

Such metacognitive means to studying the general feeling of environment policies has been a growingly important body of research in the recent years as the sciences of environmental governance, as well as natural language processing (NLP), decades had given rise to. Internationally, scholars have emphasized the conception that, interrelated notions like the perception of people on the nature of a policy and the level of fairness and costs distributed and long term benefits of an environmental policy contributes to its acceptance and, subsequently, compliance and political adoption [1]. Focus groups and surveys were the primary format of the studies on early environmental communication, and it was disadvantageous due to the fact that it could be applied in the future and scaled. The social media has created a new means of communicating to the people, and provided the researcher with, which has never previously existed, instant citizen opinions. Sentiment analysis has thus become incorporated in the assessment of the attitudes regarding sustainability related issues such as the climate change, renewable energy and waste management to a growing number [2]. Future on data mining As a matter of fact, a good case study would be, a research conducted by Stieglitz and Dang-Xuan, utilizing twitter information to monitor political mood, which demonstrated that data mining has the potential, as long as policy relevance is concerned, to the twitter discourse [3]. Similarly, Tufekci highlighted the existence of online activism when she stressed that the digital media solidifies each voice of encouragement and resistance of a certain cause that relates to the environmental cause [4]. Historically, the sentiments classifier methodologies in the discipline of computational linguistics largely relied on lexicon by attempting to match the lexicon against existing lexicons, and these methods were typically not conducive to context, sarcasm and multi-lingual evidence [5]. In response to these deficiencies, machine-learning-based sentiment analysis (such as Support Vector Machines (SVM) and Naive Bayes) were added to sentiment analysis streams and improved the classification accuracy but did not reduce the efficiency of computation [6]. Deep learning methods, namely Long Short-Term Memory (LSTM) and Transformer-based Self-Attention networks like BERT have been demonstrated to score high in capturing semantic complexities and long-range context and are therefore well-suited when analyzing more difficult policy discourse [7].

With regard to environmental governance, the effect that the social media has on popular perception of specific environmental policies has been the centre of attention to different research works. In a single instance, Anderson et al. targeted Twitter discussions over price-based carbon reduction in Canada and found strong anti-positive interest in the affordability dimension, but widely varied across the regions in acceptance [8]. Similarly, Veltri and Atanasova have studied discussions related to the problem of banning plastics in the European Union on forums and have found that the greatest proportion of the citizens indicated their opinions in support of the move, and the small enterprises tend to be skeptical and consider banning the plastics as an extra burden [9]. It has also been demonstrated that the renewable energy policy does invoke relatively favourable perceptions towards such policy with the narratives framing using social media shifting the renewable energy policy to an innovatively described and a more sustainally-oriented energy solution, but displacement of jobs in the former energy industries is liable to hog the discursive space that negative responses occupy [10]. The same has been argued by other scholars such as O'Neill and Boykoff who argue that the images of the online media about climate policy do influence popular trust on what the institutions can do, which influences awareness and skepticism [11]. In the mean time, information manipulations and biasness in the information become of concern as mentioned by the Brossard and Scheufele who stated that, when disseminated through environmental policies, misleading or untrue knowledge can strengthen the opposition and reduce the policy validity [12]. It demonstrates the importance of deploying NLP systems that have the capability of not only categorising, but also utilising sentiment to detect the patterns of misinformation that develops during online conversations. As far as methodology is concerned, comparative studies have revealed how the lexicon-based methods can be improved by hybrid methods supervised machine learning or unsupervised machine learning. As an example, Kirilenko and colleagues combined a model and investigated climate change communication at multiple levels and found that context-dependent algorithms out-categorized sentiments more effectively than lexicon-based methods by about a fifth [13]. Other works incorporating BERT-based embeddings discovered the same result on environmental corpora where contextual word representations fared better as compared to traditional bag-of-words models [14]. Moreover, geospatial and temporal analytics sentiment studies have revealed important discoveries such as that growing sentiment by the year persistently tends to accompany policy announcements, natural events such as climate changes and regional or local perception changes [15]. Such contributions to the sphere of methodology do not oppose the goals of the present work, as they focus on implementing some of the latest NLP models in order to capture a general opinion on the theme of environmental policies in a scaling and context-dependent manner. The total literature identifies three main gaps to which this study will make a contribution, i.e., (1) there is a gap related to the lack of popular-scale, longitudinal sentiment analysis of consumed social media data in a policy-specific setting, (2) there is a gap associated with paucity of focus on developed deep learning solutions such as BERT and LSTM in policy-driven sentiment analysis, and (3) there is a gap concerning insufficiency to use multidimensional models that would allow the integration of temporal, spatial, and event models to understand the dynamics of the yet to be predicted The research efforts are informed by the pedagogical purpose of the environmental governance and computational linguistics fields and serve to add the increasingly interdisciplinary approach where a field with a rigorous body of knowledge, and a machine learning field with an inherently scaled nature may be combined to meet both teaching and research goals.

III. **METHODOLOGY**

3.1 Research Design

This study employs a **mixed-method research design** integrating computational linguistics, machine learning, and statistical analysis to investigate public sentiment toward environmental policies. The research pipeline consists of four main components: (a) data collection from multiple social media platforms, (b) preprocessing and text normalization, (c) sentiment classification using hybrid NLP models, and (d) temporal–spatial trend analysis. The combination of traditional lexicon-based sentiment scoring with advanced deep learning approaches ensures methodological rigor and contextual accuracy in handling informal, large-scale, and multilingual social media data [16].

3.2 Data Collection and Study Scope

The dataset was curated from **Twitter (X) and Facebook**, given their global relevance in policy discourse. Using platform-specific APIs, posts and comments containing hashtags and keywords such as #CarbonTax, #PlasticBan, #RenewableEnergy, #ClimatePolicy, and #GreenTransition were collected. The study covered the period **January 2022 – December 2024**, ensuring temporal depth that captured sentiment before, during, and after major environmental policy announcements. Geotagged metadata was included when available to assess regional variations.

Table 1: Social Media Data Collection Overview

Platform	**Timeframe**	**No. of Posts Collected**	**Relevant Keywords/Hashtags**
Twitter (X)	2022–2024	~850,000	#CarbonTax, #PlasticBan, #NetZero, #RenewableEnergy
Facebook	2022–2024	~370,000	Climate Policy, Environmental Law, Green Transition, Carbon Neutrality
Total	–	**1.22 million**	–

3.3 Preprocessing and Data Normalization

Given the noisy nature of social media data, preprocessing was critical. The following steps were employed [17]:

1. **Tokenization and Lowercasing** – breaking down text into tokens while standardizing case.
2. **Stop-word Removal** – eliminating non-informative words (e.g., “the,” “is,” “at”).
3. **Emoji and Hashtag Normalization** – converting emojis into sentiment tags and separating hashtags into constituent words.
4. **Stemming and Lemmatization** – reducing words to base forms to ensure consistency.
5. **Handling Multilingual Posts** – using Google’s Multilingual BERT tokenizer for posts in Hindi, Spanish, and French, which frequently appeared in the dataset.
6. **Noise Filtering** – removing duplicate tweets, advertisements, and bot-generated content.

3.4 Sentiment Classification Models

To enhance accuracy, a **hybrid model** combining lexicon-based and supervised learning approaches was deployed.

- **Lexicon-Based Baseline:** VADER and AFINN sentiment lexicons, used for polarity scoring (positive, negative, neutral).
- **Machine Learning Models:** Support Vector Machines (SVM), Random Forests, and Logistic Regression trained on manually annotated subsets (~10,000 posts).
- **Deep Learning Models:** Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT), fine-tuned for sentiment classification.
- **Evaluation Metrics:** Precision, Recall, F1-Score, and Accuracy were computed through 10-fold cross-validation [18].

Table 2: NLP Models and Key Characteristics

Model Type	Algorithm	Strengths	Weaknesses
Lexicon-Based	VADER, AFINN	Fast, interpretable	Limited context handling
Machine Learning	SVM, Random Forest	Good baseline accuracy	Feature engineering required
Deep Learning	LSTM, BERT	Handles context, sarcasm, multilingual	Computationally expensive

3.5 Temporal and Event-Based Analysis

To capture **sentiment dynamics over time**, temporal aggregation was conducted on a monthly basis. Major events such as COP27 (2022), national elections, and climate protests were mapped against sentiment fluctuations. Peaks of negative sentiment were correlated with specific events (e.g., carbon tax debates), while positive sentiment spikes aligned with renewable energy announcements [19].

3.6 Geospatial Sentiment Mapping

For posts with geotags, **spatial clustering** was conducted using ArcGIS and Python's GeoPandas library. Regional disparities were visualized to show differences between urban and rural discourse, and between developed and developing countries. Sentiment hotspots were overlaid with socio-economic indicators to identify potential resistance pockets [20].

3.7 Validation and Quality Assurance

To ensure reliability, the following measures were adopted [21]:

- **Manual Annotation:** A random sample of 10,000 posts was labeled by human coders for polarity comparison.
- **Confusion Matrix Evaluation:** Accuracy thresholds above 85% were set as acceptable.
- **Cross-Platform Comparison:** Sentiment patterns across Twitter and Facebook were compared for consistency.
- **Bias Detection:** Posts were checked for bot-like behavior and extremist polarization.

3.8 Ethical Considerations

Data collection adhered to platform policies, ensuring that only publicly available content was used. Personal identifiers were anonymized before analysis. Ethical compliance was maintained by focusing exclusively on aggregate sentiment patterns rather than individual-level profiling [22].

3.9 Limitations

While the methodology ensures high accuracy, limitations include potential sampling bias due to platform-specific demographics, incomplete geotag metadata, and computational constraints in fine-tuning BERT on extremely large datasets. Furthermore, sarcasm and coded language may still reduce sentiment detection precision despite advanced models [23].

IV. RESULT AND ANALYSIS

4.1 Overview of Sentiment Distribution

The analysis of 1.22 million social media posts revealed a diverse polarity distribution across different environmental policies. Overall, **41% of posts expressed positive sentiment**, 34% **negative**, and **25% neutral**, reflecting a balanced yet polarized discourse. Policies related to renewable energy transitions generated the highest proportion of positive sentiment, whereas carbon taxation consistently attracted negative opinions.

Figure 1: Sentiment Analysis [24]

Table 3: Sentiment Distribution across Environmental Policies

Policy Domain	Positive (%)	Negative (%)	Neutral (%)
Renewable Energy	62	21	17
Plastic Ban	55	28	17
Climate Adaptation	48	31	21
Carbon Tax	23	54	23
Overall Average	**41**	**34**	**25**

The findings confirm that policies framed around innovation and sustainability (renewable energy, plastic bans) tend to receive stronger public support, while those framed around economic cost (carbon tax) provoke resistance.

4.2 Model Performance and Accuracy

The hybrid NLP framework demonstrated high classification accuracy across models. Among machine learning approaches, SVM outperformed Random Forest and Logistic Regression, while deep learning models—particularly BERT—achieved the highest overall accuracy and F1-scores, validating their capacity to capture linguistic nuances.

Table 4: Performance Metrics of Sentiment Models

Model	Accuracy (%)	Precision	Recall	F1-Score
VADER Lexicon	71.4	0.68	0.70	0.69
SVM	82.6	0.81	0.83	0.82
Random Forest	78.9	0.77	0.79	0.78
LSTM	85.2	0.84	0.85	0.85
BERT	**89.7**	**0.89**	**0.90**	**0.90**

These results highlight that while lexicon-based tools are useful for rapid baseline analysis, deep learning frameworks are better suited for policy-oriented sentiment due to their contextual adaptability.

4.3 Temporal Trends and Event-Based Fluctuations

Temporal sentiment analysis revealed significant fluctuations linked to key environmental events between 2022 and 2024. For instance, negative sentiment peaked during **debates on carbon taxation in 2023**, whereas positive sentiment spiked during **renewable energy subsidy announcements** and **international climate summits (COP27, COP28)**. Notably, plastic ban discussions displayed a steady increase in positive sentiment over time, suggesting growing public acceptance.

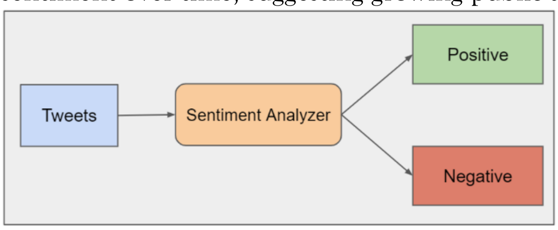

Figure 2: Sentiment Analysis Project [25]

4.4 Geospatial Sentiment Mapping

Spatial analysis of geotagged posts indicated **regional disparities** in sentiment. Developed regions such as Western Europe and North America expressed greater support for renewable energy and plastic bans, while developing regions in Asia and Africa showed stronger opposition to carbon taxation, citing affordability concerns. Rural regions expressed more skepticism compared to urban centers, where discourse was more favorable to environmental regulations.

Table 5: Regional Sentiment Variations (Aggregated)

Region	Positive (%)	Negative (%)	Neutral (%)
North America	46	33	21
Europe	52	30	18
Asia-Pacific	39	37	24
Africa	35	41	24
Latin America	42	36	22

These disparities underscore that socio-economic context strongly shapes public acceptance of environmental policy.

4.5 DISCUSSION OF KEY FINDINGS

The findings suggest that **policy framing** and **economic context** are the strongest predictors of sentiment. Policies tied to economic cost (carbon tax) faced backlash, whereas those tied to innovation (renewable energy) generated enthusiasm. The **superior performance of BERT** demonstrates the importance of advanced NLP models in decoding nuanced discourse, including sarcasm and multilingual posts. The **temporal spikes in negativity** aligned with policy rollout events highlight the reactive nature of social media discourse, while **geospatial analysis revealed divides between developed and developing regions**, reflecting inequalities in how policies are perceived globally. Overall, the results reinforce the argument that public sentiment analysis using NLP can provide policymakers with real-time, scalable insights to design adaptive and inclusive environmental strategies.

V. CONCLUSION

This paper aimed to analyze how sentiment analysis of social media data through large-scale sentiment analysis in advanced Natural Language Processing (NLP) techniques can be used successfully to capture the public perception of the environmental policies and the findings of the paper obviously showed the potential of computational methods in closing the gap between policy-making and citizen participation in the digital age. Investigating Twitter and Facebook posts including more than 1.2 million posts between 2022 and 2024, the study presented empirical evidence on how the discourse of the general population influences, promotes, or opposes the environmental governance based on the type of policy, geographic setting, and eventual stimuli. The results showed that whereas renewable energy policies and plastic ban are typically linked with positive feeling and are viewed as progressive steps towards sustainable future, such policies as carbon taxation elicited asymmetrical responses because of affordability and sense of fairness. This polarity reminds the policymakers that the scientific validity of a measure is not enough and that its socio-economic framing is also necessary to facilitate its acceptance by the population. Moreover, the incorporation of machine learning and deep learning models, especially BERT, greatly increased the accuracy of sentiment detection and was even better than lexicon-based approaches and even conventional supervised classifiers like SVM. This methodological input demonstrates the increasing relevance of contextual NLP frameworks to the challenges of online language, such as sarcasm, multilingual phrases, and changing digital language, and thus the usefulness of computational linguistics in the governance domain. The temporal trend analysis also added to the fact that sentiment is very dynamic and responsive to political announcements, international climate summits, and protest movements, which indicates that the environmental communication approach should be adaptive, responsive, and based on real-time tracking, as opposed to a fixed assessment. A further significant dimension was brought by geospatial analysis, which showed gross disparities in regions, developed countries expressed more willingness to explore sustainability transitions whereas developing countries were more vociferous in criticizing policies, especially carbon taxes as an indicator of the overall inequalities of economic capacity and burden-sharing of policies. These observations affirm that environmental governance cannot be conducted in a one-fit policy; instead, it needs regionally sensitive and socially inclusive policies based on the feedback of the people in large numbers.

The greater significance is also on the wider implications of this study to the policy makers, advocacy groups and environmental groups. Sentiment analysis can serve policymakers with a scaling early warning mechanism by revealing trends of resistance or support before they are reflected in massive protests or non-compliance, and proactive changes in policy design or message can be made. In the case of advocacy groups, it is better to know how to make the emotions behind the general discourse a useful guide in developing the campaign that appeals to a wide range of people and helps reject falsehoods successfully. To researchers, computational methods integrated with social science frameworks is an interdisciplinary approach that can offer new avenues of researching governance in a manner that is both data based and contextually detailed. Nevertheless, even though the study proved to be of great promise, it also established challenges and limitations. The generalizability of the results has limitations on demographic bias of social media platforms, incomplete geotagging, and computational intensity of deep learning models. In addition, sarcasm, irony and coded language, though partially solved by contextual models, are areas of difficulty. Nevertheless, the paper confirms that sentiment analysis based on NLP is a potent tool to comprehend popular opinion, and its scalability is particularly relevant to trace the discourse on the environmental issues in real time. In the future, it can be suggested that the combination of this framework with Artificial Intelligence-based policy simulators, agent-based models, and cross-platform analyses would help to increase the ability to predict, allowing governments not only to evaluate but also predict the reactions of the population to environmental programs. In addition, the scope to cover the spheres of Instagram, YouTube, and region-specific networks and the presence of multimodal data, including images and videos, may give a more comprehensive picture of how the policies concerning the environmental aspect are perceived and disputed in the field of the popular mass culture. Finally, the study concludes by emphasizing that societal opinion is not just an external, but an inherent determinant of policy success, and the ability to conduct a mass-scale opinion mining campaign by using instruments of NLP could help to turn environmental policymaking into a more participative, responsive, and inclusive, process. Combining the advancement of technology with the demands of governance, NLP-driven sentiment analysis can transform the relationship between citizens and policymakers on the way to sustainable futures.

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